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ADEMU WORKING PAPER SERIES

Bank funding and risk taking

Alessandro Ferrari[†]

Carmen Garcia Galindo[‡]

Matic Petricek[ŧ]

Andreas Winkler[†]

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In this paper we use a novel approach to address issues of endogeneity in estimating a causal effect of leverage on risk taking by banks. Using data on local bank office deposits and local unemployment we construct an instrument to use in a regression of leverage on a measure of risk taking constructed from new issuance of loans. The results (i.) confirm that due to limited liability banks increase their risk taking after an exogenous increase in leverage, and (ii.) that an increase in deposit supply has a direct positive effect on risk taking by banks.

JEL Codes: G11, G20, G21, G28

[†] European University Institute
[‡] European University Institute
[ŧ] European University Institute
[†] European University Institute

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March 15, 2018

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1 Introduction

There are two established, opposing theoretical results about the effect of lever-
age on risk taking by banks. First, due to limited liability expected returns on
equity investment increase with an increased riskiness of the portfolio. Because
a bank's equity holders are protected from the left tail of the returns to assets
distribution by limited liability, they have an incentive to increase the variance of
the distribution by taking on more risk. On the other hand callable demand de-
posits constitute a substantial part of bank debt. On average, almost 20 percent of

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†European University Institute

these are above the amount insured by the Federal deposit insurance corporation. This provides depositors with a strong incentive and tools to monitor and punish excessive risk taking.

There is inconclusive empirical evidence on which of the two results prevails. Our aim is to estimate a causal effect of leverage on risk taking behaviour of banks. In doing so we add to the literature by proposing two novel approaches to addressing the issues of endogeneity.

We identify two sources of endogeneity and propose a method to address them. First, an increase in leverage incentivises banks to pursue riskier investment, but at the same time the demand and supply of deposits are also affected by the banks risk taking, giving rise to the issue of reverse causality. Second, shocks, observable or non-observable, common to both assets and liabilities of a bank, if omitted, can cause a bias in the estimate of the effect of leverage on risk taking.

We conduct our empirical analysis in two preliminary stages and a final stage. In the first preliminary stage we address the issue of reverse causality by making use of bank office level data on deposits for US banks and geographically granular unemployment data. We argue that local unemployment rates are exogenous to the risk taking of a bank's headquarter and construct an instrument, an exposure to deposit supply shocks caused by changes in local unemployment rate, to use in the final stage regression of leverage on risk. However, as is often the case in the empirical literature, if risk taking is approximated by using a performance measure of existing portfolios, the issue of omitted shocks, which are common to both assets and liabilities, remains. To address this, we construct a measure of risk taking on newly issued mortgage loans. We argue that, while the existing portfolio of a bank can be affected by geographical area specific shocks which affect deposits and leverage, newly issued loans are chosen by banks after the shocks have occurred.

Therefore the riskiness of the new portfolio is a choice by the bank.

Several results are worth highlighting. First, our final stage confirms that limited liability induces banks to take on more risk after an exogenous increase in leverage. This result is robust across two different instruments. Second, the deposit supply shocks have a direct positive effect on risk taking. When banks face an increased deposit supply, the monitoring power of the marginal depositor decreases, leaving banks with more freedom to invest into a risky asset.

The rest of this paper is structured as follows: section two provides the review of relevant literature, sections three and four explain the methodology and the data. Section five presents the results. The concluding section five discusses the policy implications of the findings.

2   Literature Review

There are several theoretical papers on how banks' funding structure should impact their risk taking. Jensen and Meckling (1976) show that for a firm the decision to take on debt is equivalent to buying a call option from its creditors. When the debt is due, they can either choose to redeem the bond (buy back the firm) or not to. Since the value of such an option is increasing in volatility (see for example Black and Scholes (1973)), firms have an interest to take on higher amount of risk than without debt financing. On the other hand, as Laeven and Levine (2009) point out, requiring banks to hold more capital may not necessarily reduce these incentives if this capital is raised by issuing equity to new shareholders. Simply adding more shareholders with the same incentives may not actually alleviate the issue. Instead, shareholders may decide to make up for the higher cost of capital by taking on even more risky projects in the spirit of Koehn and Santomero (1980). Finally, Diamond and Rajan (2001) show that demand deposits can have a disciplining effect on banks. Our paper hopes to contribute to these discussions

by providing a well-identified answer about the causal effect of leverage on risk taking.

In the empirical literature, there are two ways that previous work has tried to answer the question of how leverage impacts bank risk taking. The first strain of papers attempts identification through a direct regression of a measure of leverage on some measure of risk. Altunbas et al. (2007) aim to identify the relationship between leverage and risk by means of a seemingly unrelated regression design that relates changes in capital and risk. They use loan-loss provisions as a proxy for the risk taken on by the bank and find that in their whole sample, banks with a higher equity to asset ratio will take on more risk, while the relationship is negative for the most efficient banks in the sample. Jacques and Nigro (1997) employ an approach that uses a regulatory pressure variable to identify the effect of leverage on risk, but can not refute the null hypothesis that leverage has no effect on risk taking. Koudstaal and van Wijnbergen (2012) aim to identify the effect of leverage on risk by regressing the standard deviation of returns on assets on lagged leverage while controlling for market volatility. They find that higher leverage leads to less risk taking, but that this result is entirely driven by low leverage banks. Highly leveraged banks, they find do not react to changes in leverage. Similarly to the above paper, Shrieves and Dahl (1992) find that banks take on more risk when there is a positive shock to capital by using a simulataneous regression framework. As we will argue in or methodological section below, all these papers have shortcomings in two ways: first, they fail to provide a convincing identification in the sense that leverage cannot be seen as exogenous in any of the above models. Second, as all the papers emply some measure of portfolio risk, they consider a rather noisy measure of risk taking which is also impacted by market conditions, which may in turn be impacting banks leverage decisions.

The second strain of papers in the literature attemps to provide exogenous variation to leverage by evaluating the effect of policies that impact banks ability to leverage out. Laeven and Levine (2009) find that requiring banks with an owner that holds a significant voting share to hold more capital has the effect of reducing risk taking, while the opposite is true for widely held banks. Acosta Smith et al. (2017) find that the introduction of the leverage ratio requirements in the Basel III framework did cause banks to increase their capital holdings and reduce their risk taking. Finally, Ashraf et al. (2016) showed that the introduction of risk weighted capital standards led to a reduction of bank portfolio risk in Pakistan. We add to the empirical literature by providing clean identification of the causal effect of leverage on risk taking, both by adding a new instrument for leverage and by using a measure of risk taking (a banks decision to issue certain loans) that is much less likely to be subject to outside influences than the portfolio based measure currently used in the literature. While these papers suffer from the endogeneity associated with leverage to a much smaller degree, we believe that our identification is superior as we do not need to rely on the assumption that banks did not react to news or rumors of potential policy changes prior to the implementation of the reform. Additionally, all of these papers rely once more on portfolio based measures of risk, while the present work employs a much more direct measure of risk taking.

Methodologically, our paper is related to a paper by Bartik (1993) that employs local industry shares to identify the impact of labour supply on wages. This approach has been recently formalized and discussed by Goldsmith-Pinkham et al. (2017).

3   Methodology

In this section we explain the endogeneity issues we have encountered in the analysis of leverage and risk taking, as well as our methodology to tackle them.

Before diving deeper into those issues, there are two terms we will be using with an important distinction between the two. First, we will use the term **risk taking (behaviour)** as an act of making new investment (issuing new loans) with different degree of riskiness attached to it. This is also the subject of our analysis. It is important to distinguish it from the term **riskiness of the portfolio**. This is defined by the riskiness attached to loans which have been issued in the past. Variation in riskiness of the portfolio can be caused by both risk taking behaviour and by current and past shocks absorbed by the portfolio. Although the riskiness of the portfolio is often used to proxy risk taking behaviour in the literature, the distinction will be important in understanding the issue of endogeneity and our identification.

We identify two sources of endogeneity which prevent a causal interpretation of simple regression of leverage on some commonly used measure of riskiness of the portfolio.

- Simultaneity/reverse causality: For a given level of equity, more deposits incentivise banks to riskier investment, but the demand and supply of deposits are also affected by the riskiness of the portfolio and a bank's risk taking behavior.

- Omitted shocks common to the portfolio and the deposits.

To tackle the first source of endogeneity we use data on deposits at the office level. The detailed geographical information on deposits enables us to compute bank exposure to local unemployment variation which we use as an instrument to assuring exogenous variation in leverage. This measure can still be endogenous if the measure of risk relies on the existing portfolio. If some exogenous shocks to economic activity occur, they are likely not only to affect the deposits (and leverage) through unemployment but also the riskiness of the existing portfolio. To tackle this issue, we construct a measure of risk taking based on the new issuance

of mortgage loans. We argue that while riskiness of the portfolio is affected by some shocks which are common to both deposits and assets, new issuances are a choice for banks.

In accordance with the procedure described above, we estimate the effects in two preliminary stages and a final estimation stage. In the two preliminary stages we (i.) construct an instrument to assure variation in leverage independent of risk taking and (ii.) construct a measure of risk taking based on newly issued mortgage loans. All the stages are explained in more detail after the data is presented and discussed.

3.1   Data

There are four main sources of data we use in the analysis, the bank-office level deposit data from the FDIC, and the local unemployment data from the Bureau of Labour Statistics for the first preliminary stage; the Home Mortgage Disclosure Act data on mortgage applications from the FFIEC for the second preliminary stage, and finally to we add balance sheet data from the FDIC in the final stage.

3.1.1   Summary of deposits (FDIC)

Summary of deposits data is yearly data on level of deposits at the bank office level. For every office for every bank operating in the US and insured by the FDIC, the level of deposits as of 31st of June is reported. Along with the deposit level data, the data contains detailed geographical and demographic information of every office and of the bank. The basic financial information for each bank which is added to the data is aligned with the balance sheet data, which is used in the final stage.

For the purpose of our analysis, the data for every bank is collapsed to a relevant geographical area level. In our case we will be using the Core Based Statistical Areas. A Core Based Statistical Area (CBSA) consists of one or more counties (or

7

equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting. Not all counties are a part of a CBSA. Around 10% of all observations come from counties which are not part of any CBSAs and the hold around 5% of all deposits. We compile these counties at the state level into CBSA equivalents and brand them as rural state areas. Table 1 presents some descriptive statistics from the Summary of Deposits data.

Table 1: Office Data - Summary Statistics

Year	Dep. per office (mil.)	Dep. per bank (mil.)	# of banks (thous.)	# of offices (thous.)	Avg. offices per bank
1999	44.88	188.98	10.4	68.7	6.6
2000	46.83	211.48	10.1	70.2	6.9
2001	50.26	225.29	9.8	71.1	7.3
2002	53.20	251.07	9.5	72.1	7.6
2003	58.46	280.02	9.3	78.6	8.5
2004	60.87	292.87	9.1	80.5	8.9
2005	64.47	317.24	8.9	82.1	9.3
2006	68.07	338.86	8.8	84.6	9.7
2007	68.90	365.22	8.6	87.3	10.1
2008	70.85	362.78	8.4	89.1	10.6
2009	75.94	377.62	8.2	91.9	11.2
2010	77.92	408.69	7.8	91.7	11.7
2011	84.01	458.97	7.5	98.2	13.1
2012	91.92	525.68	7.3	97.3	13.4
2013	97.92	564.01	7.0	96.3	13.9
2014	106.76	600.78	6.7	94.7	14.2
2015	114.27	660.67	6.4	93.3	14.7

3.1.2 Local area unemployment statistics (BLS)

Local area unemployment statistics provide monthly data on unemployment at the county level. Since the relevant geographical area in the first preliminary stage is the CBSA, we aggregate the statistics to the CBSA level at yearly frequency. Figure 3.1.2 plots the mean and the median value of average monthly unemployment rate of the CBSAs in the US within our sample period.

Figure 1: Mean and median average monthly unemployment rate of the CBSAs in the US
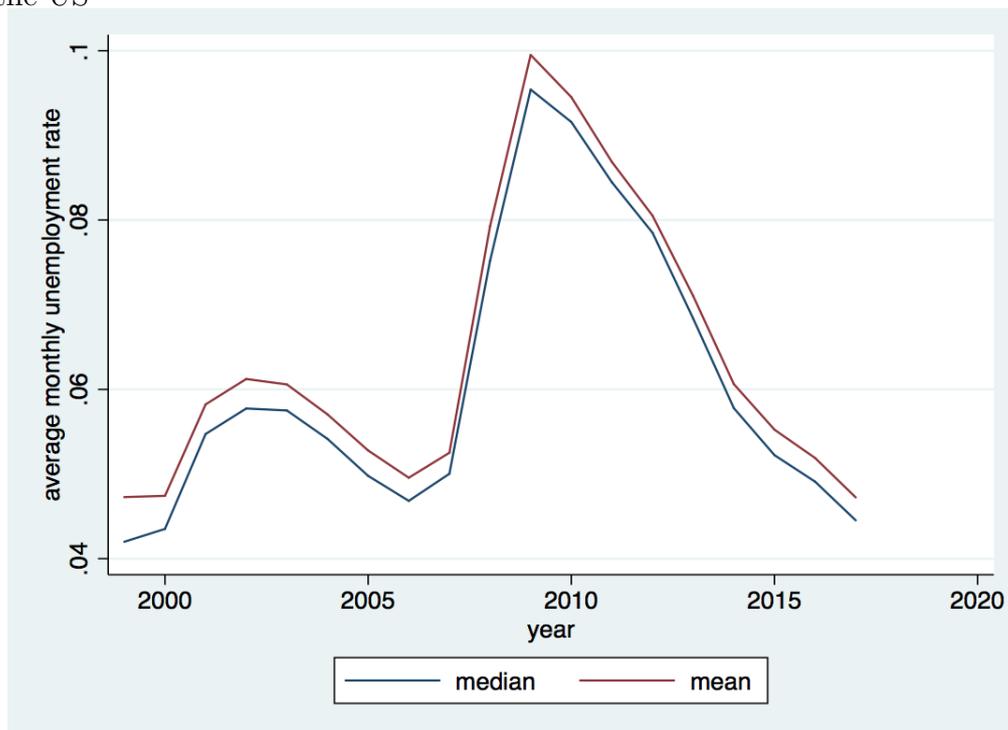
3.1.3 Home mortgage disclosure act data (FFIEC)

The Home Mortgage Disclosure Act (HMDA) obliges banks above a set threshold of assets to report on mortgage applications, lending and purchases. The reporting is done through the Loan Application Registries (LAR) and includes all mortgage loan applications within a year. Moreover, the registries contain the properties of the applicant and potential co-applicant (ethnicity, race, gender, income), the loan properties (amount, type, purpose, rate spread for some, occupancy), the properties of the property (type, census tract, etc.), the properties of the census tract (income relative to the MSA, minority population, number of housing unites, etc.), and the action taken (origination, denial and its reason, purchase by an institution like Freddie Mac).

Our construction of the measure of risk taking loosely follows DellAriccia et al. (2012) and relies on the Loan to Income ratio. The loan to income ratio is computed as the total loan amount in the application over the total gross annual

income an institution relied upon in making the credit decision[1]. To add to the methodology on a measure of risk taking we also use the data on origination. We define origination as an application which has been accepted and then either originated or refused by the applicant, a purchase of a loan, or a preapproved request. We define a non-origination as an application denied by the bank or a denied prerequest. We ignore all applications withdrawn by the applicants or applications closed for incompleteness.

The LAR data reports all applications, accepted or rejected. Table 2 provides the statistics on the origination ratio between 2004 and 2012. The share of originated loan applications decreased from 74% in 2004 to 67% in 2007. In 2009, the origination ratio increased sharply and then gradually increased to 80% in 2012. The sharp increase reflects the crisis, which has decreased the demand for loans and forced the worse potential borrowers out of the market. The remaining pool was of higher quality which increased banks willingness to lend to remaining applicants.

Table 2:   Acceptance ratio

2004	.744
2005	.729
2006	.715
2007	.677
2008	.681
2009	.767
2010	.776
2011	.766
2012	.794

[1]Gross annual income is not registered in HMDA due to four possible reasons: (i.) multifamily dwellings, (ii.) income was not registered in the loan purchase documentation, (iii.) loans to bank employees, (iv.) loans to non natural persons. These cases are excluded from the estimation as described in the methodology section

Table 3 reports the shares of prevailing reasons for rejecting a loan. Insufficient collateral, high debt-to-income and poor credit history explain the bulk of the rejection decisions. The effect of the crisis is evident in the spike of the share of rejections due to insufficient collateral in 2009 when house prices collapsed.

Table 3:   Reason for denial

	DtI	Empl. hist.	Cred. hist.	Collateral	Downpayment	Info1	Info2	Insurance	Other
2004	.131	.010	.299	.113	.0154	.0357	.100	.001	.295
2005	.122	.0111	.267	.122	.012	.051	.103	.001	.311
2006	.150	.0129	.284	.154	.017	.050	.101	.001	.229
2007	.173	.0123	.272	.193	.017	.056	.119	.001	.156
2008	.205	.0114	.265	.250	.018	.044	.0934	.003	.109
2009	.227	.0129	.209	.310	.020	.037	.0779	.004	.101
2010	.222	.0134	.202	.252	.021	.036	.117	.002	.133
2011	.214	.013	.223	.241	.021	.036	.132	.002	.116
2012	.213	.013	.233	.218	.024	.043	.139	.002	.117

On top of the loan application data, the LAR reports also the information about the loans purchased by banks. Tables 4 to 5 provide the statistics about the characteristics of all applications, the accepted applications, the rejected applications and the purchased loans.

If Loan-to-Income ratio, summarised in table 4, is taken as a relevant measure of riskiness of a loan, the purchased loans are consistently the riskier group of loans, while as expectedly the rejected loans are riskier than the accepted ones. As it is somewhat counterintuitive to consider purchased loans as riskier than the rejected ones, we can also use income as a measure of risk. As is evident in table 5, income of borrowers whose application was accepted is higher than the income of borrowers whose loans banks have purchased. As expected the income of potential borrowers whose application was rejected is the lowest.

3.1.4   Balance sheet data (FDIC)

To construct the leverage measure of banks, we use balance sheet data provided by the FDIC. The data is available at quarterly level and includes income statements as well as several performance ratios.

Table 4:   Loan-to-Income ratio

	All		Accepted		Rejected		Purchased	
	mean	p50	mean	p50	mean	p50	mean	p50
2004	2.274	2.083	2.227	2.103	2.408	2.000	2.502	2.390
2005	2.281	2.098	2.217	2.106	2.452	2.077	2.480	2.400
2006	2.188	1.974	2.109	1.951	2.385	2.038	2.322	2.233
2008	2.304	2.098	2.184	2.059	2.553	2.200	2.547	2.451
2008	2.433	2.209	2.311	2.174	2.687	2.300	2.735	2.607
2009	2.573	2.243	2.420	2.211	3.060	2.372	2.539	2.427
2010	2.430	2.139	2.309	2.115	2.846	2.244	2.673	2.540
2011	2.349	2.023	2.222	2.000	2.761	2.083	2.587	2.435
2012	2.384	2.054	2.291	2.051	2.735	2.065	2.573	2.409

3.2   First stage: obtaining exogenous variation in deposits

The aim of the first preliminary stage is to construct an instrument to assure that the variation in leverage is independent of risk taking. We do so in two ways: i) estimating shocks to local deposits caused by unemployment changes which we then aggregate for each bank computing the weighted average of these local shocks; ii) or directly computing the weighted average of unemployment changes and using this as an instrument for leverage.

To this end we use data on deposits at the bank-office level, administered by the Federal Deposit Insurance Corporation (FDIC) and the Local Area Unemployment Statistics administered by the Bureau of Labour Statistics.   The first dataset contains yearly information on the level of deposits for all offices of all banks insured by the FDIC, together with the demographic information on the office and the bank which owns it. The second dataset provides monthly unemployment figures at county level. The relevant geographical definition in our analysis is the Core based statistical area[2].

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[2]A Core Based Statistical Area (CBSA) consists of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting. Not all counties are a part of a CBSA. Around 10% of all observations come from counties which are not part of any CBSAs and the hold around 5% of all deposits. We compile these counties at the state level into CBSA equivalents and brand them as rural state areas.

The rationale behind these instruments for bank level deposit growth rates follows closely Bartik (1993), whose approach has been extensively analysed in Goldsmith-Pinkham et al. (2017). The standard idea behind this approach is that when one is interested in a parameter, say the elasticity of labour supply, using changes in wages and employment growth rates at local level, one should be concerned with the endogeneity of local employment growth. To solve this issue, the Bartik approach suggests to define an instrument as the local employment growth predicted by interacting local industry employment shares with national industry employment growth rates.

In our setting we follow a similar logic but we apply it to a different level of granularity of the data. Our potentially endogenous object is the deposit growth rate of banks. We therefore build as an instrument the predicted change in deposits for a bank in a given period as the interaction between the bank's geographical area deposit share and the change in deposits in the geographical area.

We do so in two different ways to avoid any further endogeneity concern or feedback loop between bank and area level deposit changes: i) we predict the change in deposits in a geographical area in a given period based on the change of local unemployment in that period and use this fitted value as our instrument; ii) we use the change in unemployment in the geographical area directly (not using it to predict deposits) as the instrument.

Before discussing the two approaches in further detail, key differences between our strategy and the standard Bartik instruments should be highlighted. As mentioned above, the literature employs this approach to solve endogeneity problems. In contrast, we use the geographical area shares as a mean of aggregation, not as a solution to endogeneity per se. We adopt as instrumental variables for the

leverage the "relevant" changes in local unemployment or deposit supply, where "relevant" is to be read as weighted by geographical area deposit composition. The adoption of of this specific aggregation strategy serves two distinct purposes: first and foremost is an appealing way of aggregating geographical area specific changes to the bank level; second it eliminates any further endogeneity concerns.

The two approaches are formalized below.

Instrumenting deposits: In the first method we regress the growth rate of total deposits in a geographical area on the change in the local unemployment rate. We brand the fitted values from this model at the geographical area level as shocks to deposit supply at the geographical area level. For each bank in each year we then compute the exposure to this variation in deposit supply as a weighted average of these shocks using the deposits each bank holds in a particular area as weights. This implies the following procedure,

$$\Delta dep_{i,t} = \alpha_0 + \gamma_i + \eta_t + \beta \Delta unemp_{i,t} + \epsilon_{i,t} \tag{1}$$

where $\Delta dep_{i,t}$ denotes the growth rate of deposits in a geographical area i in period t, γ_i and η_t denote geographical area and time fixed effects, and $\Delta unemp_{i,t}$ denotes a change in unemployment rate in geographical area i in period t. We call the fitted values from the model above local shocks to deposit supply. To compute the exposure of a particular bank in a particular period to these shocks, which would serve as an instrument for leverage in our final estimation, we compute the weighted average of these shocks for every bank, where then we use the deposit this particular bank holds in different areas as weights. For bank b, operating in areas $i = 1..I$, this implies:

$$\Delta \hat{dep}_{b,t} = \frac{\sum_{i=1}^{I} dep_{b,i,t} \Delta \hat{dep}_{i,t}}{\sum_{i=1}^{I} dep_{b,i,t}} \tag{2}$$

where $dep_{b,i,t}$ denotes the deposits bank b holds in geographical area i in period t. We use the measure $\Delta \hat{dep}_{b,t}$ as one of the possible instruments in the final

estimation of the effect of leverage on risk taking.

Table 3.2 presents the estimation results for equation 1. Results, as expected, prove a negative and highly significant effect of changes in unemployment on deposit growth rates at the CBSA level. An increase in unemployment change in a CBSA by one percentage point decreases the deposit growth rate in that area by 0.43 percentage points after controlling for the CBSA and year fixed effects.

Table 5: Regression table: First preliminary stage

| | (1) |
	$\Delta ln(deposits)$
$\Delta unemp$	-0.432***
	(0.117)
constant	0.0310***
Time FE	YES
CBSA FE	YES
N	21450
R^2	0.014
adj. R^2	-0.034

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2 plots the mean of the bank level deposit supply shock, $\hat{dep}_{j,t}$ across time. The figure also depicts a sharp drop in deposit supply caused by a spike in unemployment across the US.

Figure 2: Mean bank level deposit supply shock
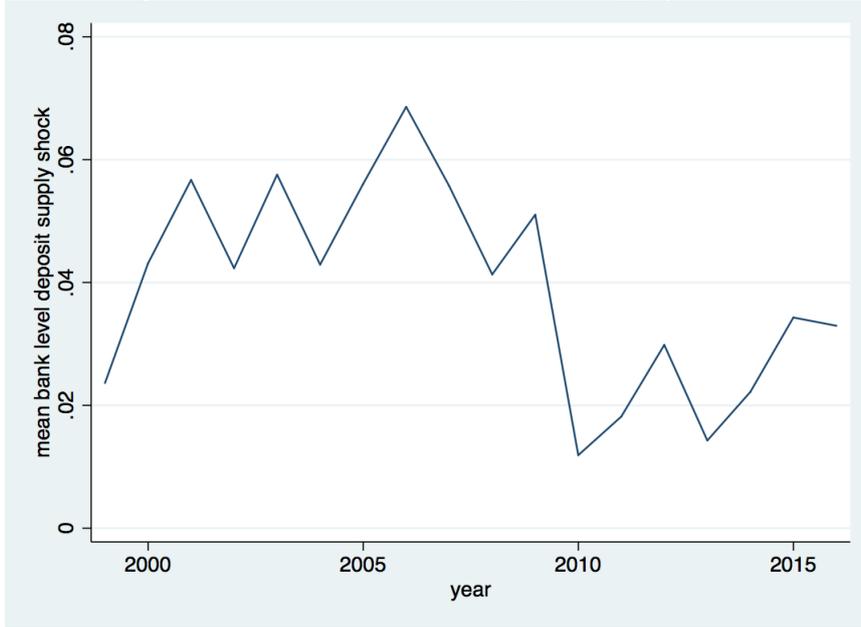
Direct local unemployment exposure: In the alternative method we directly estimate the exposure of each bank to changes in local unemployment rates, using, as before, the deposits a bank holds as weights. For bank b, operating in areas $i = 1..I$, this exposure, $\Delta exp_{b,t}$, is given by:

$$\Delta exp_{b,t} = \frac{\sum_{i=1}^{I} dep_{b,i,t}\Delta unemp_{i,t}}{\sum_{i=1}^{I} dep_{b,i,t}} \qquad (3)$$

where, as before, $dep_{b,i,t}$ denotes the deposits bank j holds in geographical area i in period t, and $\Delta unemp_{i,t}$ denotes a change in unemployment rate in geographical area i in period t. We use $\Delta exp_{b,t}$ as the second instrument in the final estimation of the effect of leverage on risk taking. Figure 3 plots the mean bank level exposure to unemployment.

Figure 3: Mean bank level exposure to local unemployment changes
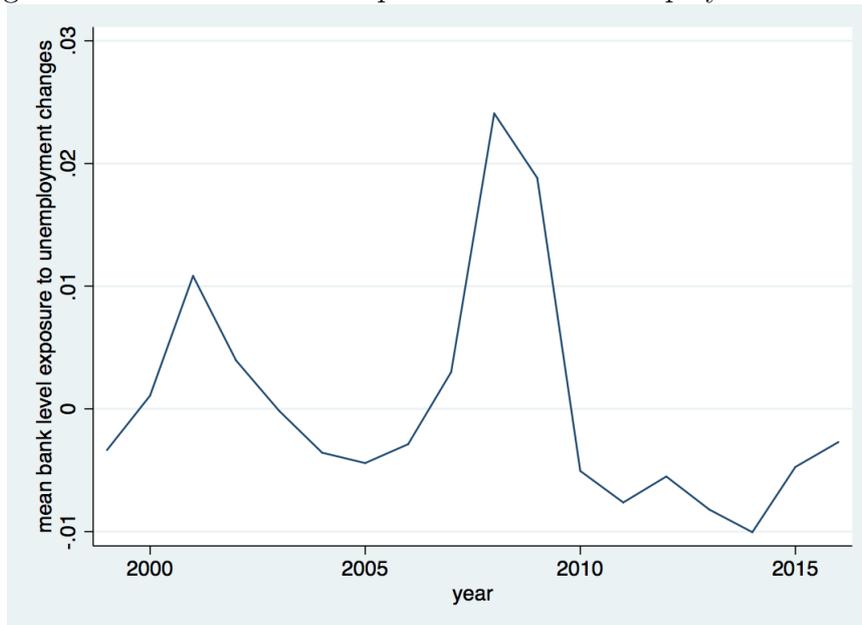
The two instrument exploit the same variation of changes in unemployment at the local level. They are not numerically equivalent due to different specifications (of the fixed effects). It is also worth noting that the second instrument does not require any estimation since it is only built through aggregation of local areas changes at the bank level. This is relevant because one may be concerned that our first instrument may suffer from generated regressor problems. As we will show later we obtain almost identical results with the two instruments.

3.3 Second stage: creating a measure of risk taking

3.3.1 Remaining endogeneity

The procedure explained above describes constructing a measure of an exogenous change in deposits and a measure of an exposure of banks to changes in local unemployment rates. Both these measures are exogenous to risk taking, but not exogenous to a measure of riskiness of the portfolio. To exemplify the issue, consider a shock to deposits in a certain area as estimated in the previous section. Such a shock is likely to impact the income of depositors. It cannot however be excluded to have impacted also the borrowers, private or corporate, in an area,

which may or may not have borrowed from the banks operating in that areas. Any measure of risk, which is based on the performance of the existing portfolio might be subject to this sort of residual endogeneity.

New issuances of loans are not subject to this endogeneity concern since new issuances can only be affected by the existing pool of potential loans. A geographical area shock can affect the existing local pool of borrowers, however it does not affect the entire pool of potential borrowers. New issuance of a loan is a choice for a bank and the riskiness of new issuances proxies risk taking behaviour.

3.3.2 Creating a measure of risk taking

To this end we construct a measure of risk taking based on the issuances of new mortgage loans based on the Home Mortgage Disclosure Act (HMDA) dataset, administered by the Federal Financial Institutions Examination Council (FFIEC). It is a yearly dataset on the population of mortgage applications to banks and other mortgage lenders with detailed information on the borrower and loan characteristics. We take the riskiness of new mortgage lending as representative of risk taking on the entire portfolio.

To construct a measure of risk taking behaviour by banks, we estimate the responsiveness of loan issuance of each bank in each year to riskiness of the borrower and the loan. As a measure of riskiness of the loan and the borrower we use the Loan-to-Income (LtI) ratio computed from the HMDA dataset for every loan application. This follows loosely DellAriccia et al. (2012), where LtI is used directly as a measure of risk in their analysis of lending standards. Our methodology

implies the following model[34].

$$Origin_{t,b,j} = \gamma_t^0 + \gamma_{t,b}^1 LtI_{t,b,j} + \epsilon_{t,b,j} \qquad (4)$$

where $Origin_{t,b,j}$ denotes a binary loan origination variable which takes the value $Origin_{t,b,j} = 1$ if the application in period t to a bank b by a borrower j is accepted and loan is originated, and takes the value $Origin_{t,b,j} = 0$ if the application is rejected and the loan is not originated. γ_t^0 captures the effect of the macroeconomic situation in period t for all banks, such as market liquidity and regulation. Finally, for every bank b in every period t we also obtain an estimate of the risk responsiveness $\gamma_{t,b}^1$ based on Loan-to-Income of all applicants j from 1 to J, which serves as a measure of risk taking behavior by banks.

Figure 4 plots the risk measure for the banks included in the analysis over the years. The distribution has a mean of 0,038 with a standard deviation of 0.129.

Figure 4: Distribution of the risk measure to LtI

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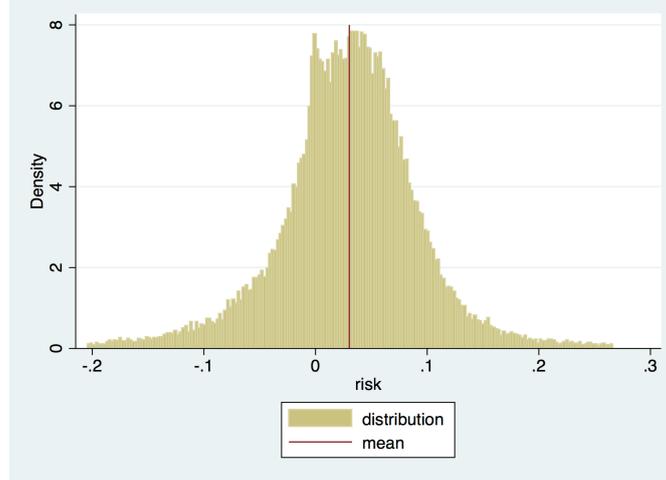
[3]In order for γ_t^0 to capture the macroeconomic conditions affecting the origination choices, we estimate the model for all banks reporting to the HMDA dataset but only use the $\gamma_{t,i}^1$ for banks included in the final regressions. This implies including all the loan applications in the HMDA reporting in the estimations. The number varies between 17 million applications and 40 million application which constrains us to estimating the model as a linear probability model.

[4]This measure is joint work with López-Quiles and Petricek (2018)

3.4 Final stage: the effect of leverage on risk taking

In the final stage we use the two instruments, explained in detail above, to estimate the effect of leverage on risk taking. As argued before the instrumented deposits and the direct measure of exposure to local unemployment shocks are exogenous to risk taking. The instruments allow us to estimate two effects: (i.) the effect of the two instruments on leverage, and (ii.)the effect of leverage on risk taking.

More specifically we run the following two specifications:

$$\hat{\gamma}_{b,t} = \beta_0 + \beta_1 lev_{b,t} + \eta_j + \delta_t + \epsilon_{bt} \tag{5}$$

Where lev_{bt} is the endogenous variable, η_b are bank fixed effects and η_t are time fixed effects. This equation is estimated by IV, where the endogenous variable lev_{bt} is instrumented with one of the two instruments: either $\Delta\hat{dep}_{bt}$ or Δexp_{bt}, depending on the model. It is also estimated by OLS, in order to compare the coefficients of interest.

To investigate the direct effect of an exogenous change in deposits on risk taking behaviour we estimate

$$\hat{\gamma}_{b,t} = \beta_0 + \beta_1 \Delta\hat{dep}_{bt} + \eta_b + \delta_t + \epsilon_{bt} \tag{6}$$

An alternative model for equation (6), in which exposure to local unemployment shocks is used instead of exogenous deposits, is considered too.

The results of the estimations are presented and discussed in the next section.

4 Results

Table 6 presents the results of the estimations for both instruments. Column (1) shows the biased OLS estimate of regressing the risk taking measure on leverage.

Columns (3) and (4) present the results using the exposure to changes in unemployment as an instrument, while columns (6) and (7) present the deposit supply shocks as an instrument. Columns (3) and (6) show the first stage of the two IV regressions, while Columns (4) and (7) show the second stage. Columns (2) and (5) display the direct effect of the unemployment IV and the deposit growth IV on the risk measure. Both sets of results are consistent both in terms of sign and numerically, so we will focus on the latter in explaining them. All standard errors are clustered at the bank level.

First we find that the naive OLS approach severely underestimates the effect of leverage on risk taking behaviour, the result is one order of magnitude lower than the IV estimation outcome. This bias may go some way towards explaining findings in the previous literature that leverage leads to less risk taking, or has no effect (see for example Altunbas et al. (2007) and Jacques and Nigro (1997)).

Second we find that an increase in deposit supply leads to higher risk taking by banks. A possible explanation for this result is that when deposit supply increases the monitoring power of the marginal depositor decreases, allowing banks to take on more risk. Alternatively one can think of a "shadow price of risk" story, meaning that the expected cost of taking on more risk decreases in an environment where the deposit supply is larger. Finally, and most importantly, all our results provide convincing evidence for the narrative of a positive effect of leverage on banks' risk taking due to limited liabilities.

Table 6: Regression table

	(1) OLS Risk Measure	(2) OLS Risk Measure	(3) IV-S1 Leverage	(4) IV-S2 Risk Measure	(5) OLS Risk Measure	(6) IV-S1 Leverage	(7) IV-S2 Risk Measure
Leverage	0.000467** (0.000158)			0.00874** (0.00284)			0.00802** (0.00268)
IV Δ Unemployment		-0.108** (0.0376)	-12.37*** (1.424)				
IV Δ Deposits					0.230** (0.0852)	28.63*** (3.107)	
Constant	0.0414*** (0.00130)	0.0441*** (0.000830)	6.378*** (0.0344)	-0.0116 (0.0182)	0.0390*** (0.00213)	5.742*** (0.0802)	-0.00707 (0.0172)
Time FE	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES
Observations	71702	71540	71539	71539	71540	71539	71539
R^2	0.105	0.104	0.066		0.104	0.066	
Adjusted R^2	0.104	0.104	0.066		0.104	0.066	

Bank clustered standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We also investigated the possibility of nonlinear effects of leverage on risk taking by running our IV regression through 2SLS and interacting the predicted endogenous variable with dummmies denoting different deciles of the leverage distribution. We found no significant pattern in the estimation and that most coefficient on these dummies are not statistically significant. The takeaway of this analysis is that the effect of leverage in our data does not significantly vary along the distribution.

Quantitatively our results state that a one point increase in leverage generates an .008 increase in our risk taking measure. The mean of the risk measure in our data is .03, which implies that a one point increase in leverage produces a 26% increase risk taking when compared to the average. For a specific example, assume that two banks are identical except for their leverage ratios, which differ by one point. Assume that they receive the same application for a mortgage loan with average Loan-to-Income. Our estimates suggest that this application has an expected probability of being originated in the bank with the lower leverage of $\gamma_0 + \gamma_i LTI$ whereas the expected probability of origination for the more leveraged bank is $\gamma_0 + (\gamma_i + .008)LTI$. Evaluating these probabilities at the average of our

estimates and at the average loan-to-income we obtain that the more leveraged bank has a 3% higher probability of originating the loan. Note also that this wedge between the probabilities of acceptance increases with loan-to-income. Meaning that the higher the loan-to-income of the applicant the larger the difference in expected acceptance probabilities between the more and less leveraged bank.

Our results have policy relevant implications in terms of the aggregate level of risk in the banking system. The estimations show that more levered banks are more likely to take on riskier projects due to limited liability incentives which implies that curbing leverage has the added benefit of reducing banks' risk taking, thereby producing a more resilient banking system.

In recent years a new trend of modelling banks as deposit creators has risen. In this view banks are not constrained by the supply of deposits since deposits are created upon loan origination. The relevant constraint for banks then becomes the availability of investment opportunities. In a world in which in which there is no deposit supply, but only loan demand, all our results carry through with a different interpretation. Namely what we have denoted throughout this paper as a deposit supply shock should then be reinterpreted as an exogenous change in funding demand by entrepreneurs. This is consistent since in such a world any observed deposit is just an originated loan. Our results would then suggest that as loan demand exogenously increases banks take on riskier projects.

5 Conclusions

This paper addresses the question of the causal effect of exogenous changes in leverage on banks' risk taking behaviour. We do so by constructing a set of instruments to overcome the endogeneity problems resulting from the potential simultaneity and reverse causality between risk decisions and the deposit market conditions.

We instrument exogenous changes in the leverage by building two instruments: i) one based on the geographical area unemployment changes; ii) one based on the geographical area deposit supply changes. In both cases we aggregate them using the local deposit share of banks.

We then build a new measure of risk taking behaviour based on the responsiveness of origination decisions to a measure of risk of loan applications (loan-to-income). We compute this measure at the bank/year level and use it as our outcome.

Our empirical analysis suggests that exogenous increases in leverage incentivise banks to take on more risk, i.e. to originate loans with higher loan-to-income. This result is consistent with a limited liability and moral hazard story put forth by some of the theoretical literature. This result is novel in the empirical literature on leverage and risk taking, as previous works have found no relation or a negative relationship between leverage and risk. Furthermore, we find that exogenously increased deposit supply allows banks to take on more risk. These results have relevant policy implications in that they suggest that any measure that would reduce banks' leverage would also decrease incentives to invest in risky assets, thereby considerably reducing systemic risk.

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